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Gross polluters for food shopping travel: An activity-based typology

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A B S T R A C T

To address the failure of sustainable transport policies to bring about significant change, researchers have proposed to 'tame the few', targeting the minority sectors of the population responsible for a disproportionate amount of emissions. At the same time, activity- and practice-based approaches are increasingly proposed as the way forward for transport and energy research. In this article, we develop an approach inspired by both developments, by focusing on the car- and carbon-intensive food shopping practices of the 20% of households with the longest car travel distance as recorded in the National Travel Survey of Great Britain (NTS 2002-2010) for this activity. We present a four-cluster typology of gross polluters, highlighting the crucial role of frequency and the existence of a small but growing group of low-income, older households with 'Shopping intensive' travel patterns. These results suggest that, while the households with the worst climate impact have a distinct socio-demographic profile, broader sections of the population are recruited into gross polluting patterns of food shopping travel. Also, while built environment policies remain key, significantly reducing transport emissions in this area requires a broader approach, taking into account the relationships between food shopping and eating practices.

1. Introduction

With transport the only sector where greenhouse gas (GHG) emissions have increased since 1990 in the EU-27 (EC, 2012), there is clearly a chronic gap between goals and accomplishments in the field of sustainable transport policy. According to Gössling and Cohen (2014), this is mainly explained by the existence of strong 'transport taboos' – i.e. "fundamental, yet ignored (...) barriers to the implementation of significant (climate) policy in transportation" (p. 198). One of these 'taboos' is the unequal contribution of different sectors of the population to transport externalities.

As Gössling and Cohen argue, "a minor share of highly mobile travellers, mostly from higher income classes, are responsible for a significant share of the overall distances travelled, as well as emissions associated with this transport" (2014, p. 199). A growing number of academic studies has highlighted the very skewed distribution of transport GHG emissions (e.g. Aamaas et al., 2013; Brand and Preston, 2010; Brand et al., 2013; Büchs and Schnepf, 2013; Gough et al., 2011; Preston et al., 2013). On this basis, researchers have argued that, for reasons of fairness and efficiency, 'gross polluters' should be targeted by tailored policy measures (Brand and Boardman, 2008; Chatterton et al., 2015; Mattioli, 2016). However, policy makers have so far steered clear of targeting high mobility patterns with specific policy measures (Gössling and Cohen, 2014). So, while the skewed distribution of transport GHG emissions could be construed as an opportunity to take advantage of, it is currently remarkably absent from the transport policy agenda. This in turn is a barrier to the achievement of sustainable transport.

While the research evidence on the skewed distribution of transport emissions is robust and conclusive, most studies so far have focused on overall travel, with only limited analysis disaggregated by travel purpose. This is in contrast with a shift in transport and energy research towards studies that focus on specific activities or practices. In transport research, the case has been made for activity-based approaches to travel analysis (Pinjari and Bhat, 2011) and for the close investigation of travel purposes other than commuting (e.g. shopping, leisure, etc.), which account for large travel distances (Anable, 2002, 2005; Schlich et al., 2004). Similarly, in the broader energy research field, there is increasing attention for the end uses of energy (Day et al., 2016; Knoeri et al., 2015; Shove and Walker, 2014). So far, however, such studies have not given much attention to patterns of energy consumption at the higher end of the spectrum of carbon emissions.

In this article, we fill this gap by focusing on a specific activity responsible for a substantial amount of car travel (food shopping) and, at the same time, on the 20% of households responsible for most of it. Based on travel survey data for Great Britain (NTS

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2002-2010 dataset), we investigate patterns of weekly food shopping travel among these households, describing them in terms of frequency, concentration, distance and use of alternative modes. The underlying research question is: which patterns of food shopping travel by car are responsible for most of resulting carbon emissions?

The article is structured as follows. In Section 2, previous studies on transport emissions distribution are reviewed, along with activity- and practice-based approaches in transport and energy research. The case for focusing on food shopping is also made, and previous research findings in this area are summarised. Section 3 introduces the approach, data and methods used. The findings in Section 4 are discussed in Section 5, and implications for transport policy are drawn (Section 6).

2. Background

2.1. Transport emissions distribution

There is now substantial evidence on the social variation of GHG emissions both in general (Baiocchi et al., 2010; Büchs and Schnepf, 2013; Druckman and Jackson, 2008; Girod and de Haan, 2009; Gough et al., 2011; Preston et al., 2013) and specifically for transport (Aamaas et al., 2013; Brand and Boardman, 2008; Brand and Preston, 2010; Brand et al., 2013), from which the following conclusions can be drawn.

First, the distribution is highly unequal, with gross polluters responsible for a disproportionate share of total emissions, and this is even more pronounced for transport emissions. Brand and Preston (2010), based on a study of transport emissions in Oxfordshire (UK), find a '60-20 rule', "surprisingly similar across units and scales of analysis" (p. 9), whereby 60% of emissions are produced by 20% of the population. Second, car and air travel account for an overwhelming share of passenger transport emissions, while local public transport is insignificant overall.

Third, while income is the dominant explanatory factor of varying levels of overall emissions (and the association is even stronger for transport), other factors are significantly related with transport emissions. The most recent and comprehensive study for Britain (Büchs and Schnepf, 2013) finds that household size is positively associated with household transport emissions but negatively correlated with *per capita* emissions, indicating economies of scale. Households with children and male headed households also have higher emissions. Age has a curvilinear relationship with emissions, with highest values in the working age band, and indeed emissions increase with employment. Other studies have found a positive association with car ownership, while the association with urbanisation is negative (for daily travel). Given the strong link between travel distances and emissions, the relationships mirror those with travel distances (Holz-Rau et al., 2014).

Finally, despite these associations, the investigated determinants typically account for only a relatively small share of the observed variation, i.e. there is high variation within socio-demographic groups, and notably within high emission and high income groups. Conversely, there are pockets of high emissions among low income groups. Therefore, Brand and Boardman have highlighted the need for "alternative or complementary segmentation methods" (2008, p. 236).

Studies in this area are driven by concerns for the distributional implications of carbon reduction policies, typically concluding that a carbon tax would be regressive, although less so for transport emissions (given the steeper income gradient). Therefore, Brand and Boardman (2008) argue for a "taming of the few" approach whereby "(transport) policy needs to target the gross polluters (...) to seek out these differences, identify the causes and target these causes directly" (p. 234).

One shortcoming of this literature is that it generally focuses on total transport emissions, with little insight for the activities that are travelled to. To the best of our knowledge, the only exception is the study by Brand et al. (2013), which estimates CO_2 emissions from motorised passenger travel for different travel purposes, based on a non-representative survey in the UK. Relevant to this study, the authors find that "travel for shopping or personal business" produces an important share of emissions (19%), but these are more equally distributed among the population than other travel purposes, and harder to predict based on socio-demographic and built environment variables. Overall, then, there is only limited evidence on the activity patterns underlying high levels of transport emissions. This is in contrast with an increasing importance of activity- and practice-based approaches in transport and energy research.

2.2. Activity and practice-based approaches

While traditionally transport research has studied travel behaviour with little regard to the activities it is embedded in, some approaches acknowledge that travel is a derived demand, i.e. that in order to understand travel, it is necessary to understand individual and household activity participation. Activity-based approaches to travel analysis and modelling (Bhat and Koppelman, 1999; Buliung and Kanaroglou, 2007; Kitamura, 1988; Malayath and Verma, 2013; McNally and Rindt, 2008; Pendyala and Goulias, 2002; Pinjari and Bhat, 2011) attempt to "better understand the behavioural basis for individual decisions regarding participation in activities in certain places at given times", aiming to include "all the factors that influence the how, where and why of performed activities" (Bhat and Koppelman, 1999, p.119). To date, several studies into travel for shopping have adopted an activity-based approach (e.g. Bhat et al., 2004; Jiao et al., 2011; Krizek, 2003; Schmöcker et al., 2008).

In the energy research field, acknowledgement that technological innovation alone is insufficient (Anable et al., 2012) and dissatisfaction with cognitivist approaches to behaviour change (Shove, 2010) have led to increasing interest for detailed accounts of 'what people do'. Shove and Walker (2014) make a compelling case for "reinstating fundamental questions about what energy is for in research and policy" (p. 16), by considering energy as an ingredient in the reproduction of *social practices*. Shove et al. (2012) define practices as "routinized types of behaviour" (Reckwitz, 2002, p. 249) consisting of three kinds of elements – materials, competences and meanings – that are integrated when practices are performed. At the same time, practices shape each other and might connect to form 'complexes' of practices that "depend upon each other (...) in terms of sequence, synchronisation, proximity or necessary coexistence" (Shove et al., 2012, p. 87). For example, the evolution of eating practices is strongly linked to the dynamics of tv watching, food preservation and freezing (p. 87–94) and arguably food shopping. Also, practices compete with each other for the finite resource of time (p. 127), and there is indeed some evidence that energy-intensive but time-saving practices (such as pre-prepared meals) are increasingly common in contemporary 'time-squeezed' societies (Jalas, 2005; Shove, 2003; Warde et al., 2007). Indeed, sustainable practices scholars have recently proposed a research agenda focused on temporality, bringing to the fore questions of rhythm and frequency of energy-consuming practices (Walker, 2014).

While there have been calls to introduce a social practice approach in transport research (Cairns et al., 2014; Mattioli et al., in press; Watson, 2012), most studies so far have focused on driving, cycling and car sharing as practices per se (Kent and Dowling, 2013; Shove et al., 2012; Watson, 2012). However, transport is a derived demand, i.e. a certain amount of mobility is integral to most practices. In this article, we focus on the travel arising from a single social practice, food shopping, aiming to bring to light high carbon patterns.

It is important to point out that our data in this study do not allow us to investigate directly the materials, competences and meanings associated with food shopping, nor the links with other related practices (eating, cooking, etc.). It does allow us, however, to detect "traces of practices" (Shove, 2009) in terms e.g. of frequency, travel time and distance. We use these traces to give a rich description of patterns of travel to the shops, which we then discuss in light of existing research. In that sense, the social practice framework has informed the *interpretation* of our findings, more than the data analysis.

2.3. Food shopping travel

Beyond the aim of investigating a specific activity, there are substantive reasons to focus on food shopping in this study. First, it accounts for a substantial amount of travel: recent figures for England (DfT, 2014) suggest that shopping (in all its guises) is the most common trip purpose, accounting for 20% of trips. Our calculations based on the NTS 2002–2010 dataset show that *shopping for food* accounts for just under half (48%) of shopping trips.

While shopping trip rates have fallen for two decades, average length has increased, which has been interpreted as indicating "a switch from more frequent, short shopping trips on foot to longer, less frequent car trips" (RAC, 2006, p. 15). This is probably related to historical trends in the food retail sector such as concentration (in fewer, larger stores) and the rise of out-of-town development (BBSR, 2011; RAC, 2006). These have raised concerns about increasing car dependence and associated increasing emissions as well as the rise of 'food deserts' (Wrigley, 2014). As a result, local access to grocery stores is a prominent part of compact city policies (OECD, 2012), aiming to enable shopping without the car (BBSR, 2011), and this has been reflected in UK spatial planning policy since the 1990s (RAC, 2006; Wrigley and Lambiri, 2014). This policy may now be starting to bear fruit as the UK has seen an apparent shift of preferences away from 'one-stop' out-of-town supermarkets towards 'convenience' local shops (Wrigley and Lambiri, 2014) which, when combined with the rise of online shopping and delivery, has directed increasing policy attention to food shopping.

However, the evidence is mixed on the impact of providing local shopping opportunities on reductions in car travel. While some studies (BBSR, 2011) find a strong effect of the built environment on shopping travel behaviour, other cast doubts on the potential of densification policies (Handy and Clifton, 2001; Krizek, 2003), suggesting that people are likely to patronise distant food shops even when these are available in proximity. Also, the benefits of the substitution of travel to the shops with online shopping and home delivery are intensively debated, with studies showing that, for a single purchase (and depending on numerous assumptions), home delivery is less carbon intensive than travelling to the shops (Edwards et al., 2010), but at the level of individuals and households, e-shopping seems to have a complimentary, rather than a substituting effect on physical travel (Cao et al., 2012).

While the environmental impacts of food shopping travel have mostly been addressed from a spatial perspective, its *frequency* has been investigated within retail and transport modelling research. Indeed, food shopping is a frequent activity, with individual inter-shopping intervals typically well below seven days (Bhat et al., 2004; Jiao et al., 2011; Kim and Park, 1997). While individual frequencies differ, it is often presumed that grocery shopping behaviour is designed in a 1-week cycle (Sugie et al., 2003). Interestingly travel frequency has not, to our knowledge, been investigated in direct relationship with resulting emissions. Historical studies suggest that increasing motorisation has contributed to a shift from daily to weekly 'bulk' shopping (Jessen and Langer, 2012). However, modelling research shows that car use is only one amongst several factors affecting food shopping frequency (Bhat et al., 2004).

Overall, existing evidence suggests that patterns of 'travel to food shopping' may vary greatly in terms of destination, frequency and mode of travel. Each of these attributes can be affected by distances to the shops but also, clearly, by other factors such as e.g. the eating and food preservation habits of those who make the purchase and the characteristics of the products that are bought. Also, there may be trade-offs between different aspects of travel, e.g. trips may be shorter, but more frequent. This makes it important to detect which 'genres' of shopping contribute the most to transport emissions, and the role of frequency in that. In the empirical part of this study, we define patterns of 'travel to food shopping' as different combinations of distance, frequency and mode of travel. We identify distinct patterns among the group of households responsible for most of car driver distance (and related emissions) for this travel purpose.

3. Approach, methods and data

3.1. Approach

The data analysis is structured as follows. First, we define the 'analysis sample' (Section 4.1). This includes households in the 'top 20%' of weekly car driver distance for food shopping, stratifying within types of area. We demonstrate that this group largely overlaps with the 'top 20%' of the highest CO_2 emitters for this travel purpose. Second, we use logistic regression to illustrate to what extent the analysis sample differs from the rest of the sample in terms of key socio-demographics, car availability and self-reported accessibility to grocery shops (Section 4.2). Third, we use cluster analysis to bring to light patterns of weekly food shopping travel within the analysis sample (Section 4.3). The goal is to highlight patterns of food shopping travel by car that are particularly distance- and carbon-intensive. In Section 4.3, we profile the clusters in terms of variables that were not used for the clustering. These include key socio-demographics, car availability, accessibility to grocery shops, residential location and food shopping trip rates by day of the week. The goal is to explore the correlates of the car-intensive patterns of food shopping identified in the previous step. Finally (Section 4.4), we illustrate differences between clusters in terms of CO_2 emissions. All differences between clusters are tested with Chi-square or one-way ANOVA tests.

Given the focus in this study on food shopping, our analysis refers to surface travel and related emissions only, excluding air travel. This is in contrast with studies of total transport emissions (e.g. Aamaas et al., 2013; Brand and Boardman, 2008; Brand and Preston, 2010) which have generally included air travel. Also, our analysis does not take into account online shopping and the impact of home-deliveries on emissions. Therefore, our analysis refers to *surface passenger travel for food shopping*, as reported in the NTS dataset.

3.2. Data

Since 2002, the National Travel Survey of Great Britain (NTS) has been carried out on a continuous basis (repeated cross-sectional design) on a sample of about 9000 households per year (corresponding to approximately 21,000 individuals). The survey is representative for Great Britain (Northern Ireland is excluded). The sampling method is based on a two-stage design, whereby primary sampling units (corresponding to postcode sectors) are randomly selected within regional strata, and addresses are randomly selected within primary sampling units (Hayllar et al., 2005).

A unique feature of the British NTS is that it includes information on the trips of all members of the sampled households over seven consecutive days, distinguishing 23 trip purposes including food shopping. This has several advantages: first, given the high frequency and the importance of 1-week cycles for food shopping, we can reasonably assume that the behaviour reported during the travel diary week is a good proxy for routine behaviour. This would be unreasonable if a less frequent activity (e.g. non-food shopping) was considered, or a shorter travel diary was available. Second, food shopping is best analysed at the household level, as the shopping behaviour of a household member is crucially dependent on that of the others.

In defining the analysis sample (Section 4.1), we use information on car driver trips only, as these are responsible for the overwhelming majority of road passenger transport emissions and, as illustrated below, this applies to food shopping as well. The NTS includes information on all household vehicles, which can be linked to trips. Using an approach similar to that of Preston et al. (2013), we applied the appropriate DECC & DEFRA CO_2 conversion factors[1] for each NTS wave to all trips in the data set. For private vehicles, GHG emissions were allocated to the driver and not shared among driver and passengers. We used information about vehicle type (car, motorbike, van, etc.), type of fuel (petrol, diesel, etc.), size of vehicle and engine capacity to assign different factors to different types of vehicles. Therefore, our analysis takes into account differences in CO_2 emissions between different types of private vehicles. For public transport trips, mode-specific factors were assigned to trips made with different modes (local buses, coaches, trains, light rail, etc.). All walking and cycling trips were assigned a factor of 0 kg CO_2 per km. For each trip in the dataset, we obtained CO_2 emissions by multiplying trip distance by the CO_2 emission factor.

With the method described above, we are able to estimate, for each household, the total amount of CO_2 emitted during the travel diary week for different travel purposes, including food shopping. However, we have chosen not to base the selection of our analysis sample on this measure, preferring instead to rely on car travel distance to keep the analysis grounded on 'what people do', and because of inconsistencies and missing information in the vehicle dataset that increase the uncertainty of estimated emission values. Therefore, information on CO_2 emissions is used to triangulate our results, rather than as the foundation of the analysis.

For the following analysis (unless otherwise noted), we have used pooled data from the NTS 2002-2010 database (DfT, 2012) – enabling larger sample size (73,550 households), more disaggregate analysis and more robust estimates than would be possible for individual years – from which we have selected the analysis sample.

4. Findings

4.1. Analysis sample definition

Fig. 1 shows curves for the values of 100 percentiles of household week *car driver* distance for food shopping, one for each type of area (ranging from London to rural areas). The flat part of the curves shows that a large number of households (ranging from 35% in rural areas to 68% in London) have zero car driver miles for food shopping in the travel diary, as a result of having made either (i) no food shopping trip during the week; or (ii) only food shopping trips by alternative modes (including as car passenger). The exponential shape of the curves suggests that most travelled distance is concentrated among a minority of households, and this applies equally to all types of area, in accordance with the findings of Brand and Boardman for CO_2 emissions (2008, p. 231). However, there are strong differences in level between the curves, shifting upwards as urbanisation decreases (although they overlap for urban areas over 25,000 inhabitants outside of London).

The graph depicts two coexisting phenomena: the extremely unequal contribution of different households and the effect of the built environment on travelled distance. In this study we are more interested in the skewed distribution than in built environment effects, which are an already much researched subject (Ewing and Cervero, 2010). For this reason, we control for urbanisation by selecting households who are in the top 20% of travelled distance *within their type of area* (i.e. right of the dashed vertical line in Fig. 1). In the following, we refer to this subsample as the 'analysis sample'. The reason for this stratification is that we aim to investigate what it is in the households' weekly food shopping patterns that explains long car driver distances *relative to the distribution typical of that type of area*. Most emphatically, this does not mean denying the impact of urbanisation: much to the contrary, we consider it so important that one needs to control for it to bring to light differences in patterns of food shopping. The shape of the curves in Fig. 1 suggests that these are at least as important for the environmental impact of food shopping travel.

The analysis sample consists of 14,587 households and, while it includes 22.8% of individuals, it is responsible for 70.4% of car driver distance and 65% of CO_2 emissions for food shopping travel. Using the same method described above, we also ranked households according to their CO_2 emissions for food shopping travel within each type of area, and selected the top quintile. The two 'top 20%' samples largely overlap, with 88.3% of households in the 'high distance' group also included in the 'high CO_2' group. Further analysis shows that 99.2% of households who are in the top quintile of distance but not of emissions are in the eighth decile of the CO_2 distribution within their area, thus only barely missing inclusion in the sample. Overall, this strongly confirms that our analysis sample consists of 'gross polluters' for food shopping travel, and that car travel distances are a powerful proxy for CO_2 emissions for daily mobility.

4.2. Regression analysis

In (Appendix Table A1) we report the results of logistic regression models for the probability of being in the top 20% of car driver distance for food shopping travel. Given how we have defined the analysis sample, we estimate seven separate models, i.e. one for each type of area. The predictors include socio-demographic and accessibility variables which have been included in previous studies of transport emissions distribution (cfr. Section 2.1). The results suggest that household size, car availability, income and age are positively associated with the probability of being in the 'top 20%', while the presence of children and of a female household reference person (HRP) reduce the probability. Overall, the models' predictive power is rather low, as attested by the values of McFadden's Pseudo-R^2. However, R^2 values increase as one moves from rural areas (0.04) towards London (0.16). This can be explained as follows: in the more urban areas the motorisation rate is lower, and so there is a greater overlap between the 'top 20%' group and households with cars. As a result, in these areas the model picks up mostly the effect of car ownership.

To control for this effect, in Table A2 we present the results of a second group of models, based on the subsample of households with at least one car. The results are broadly similar, even though the coefficients associated with presence of children, sex of HRP

[1] Available from http://webarchive.nationalarchives.gov.uk/20120315175222/http:/www.defra.gov.uk/environment/economy/business-efficiency/reporting/ (accessed 14 December 2014).

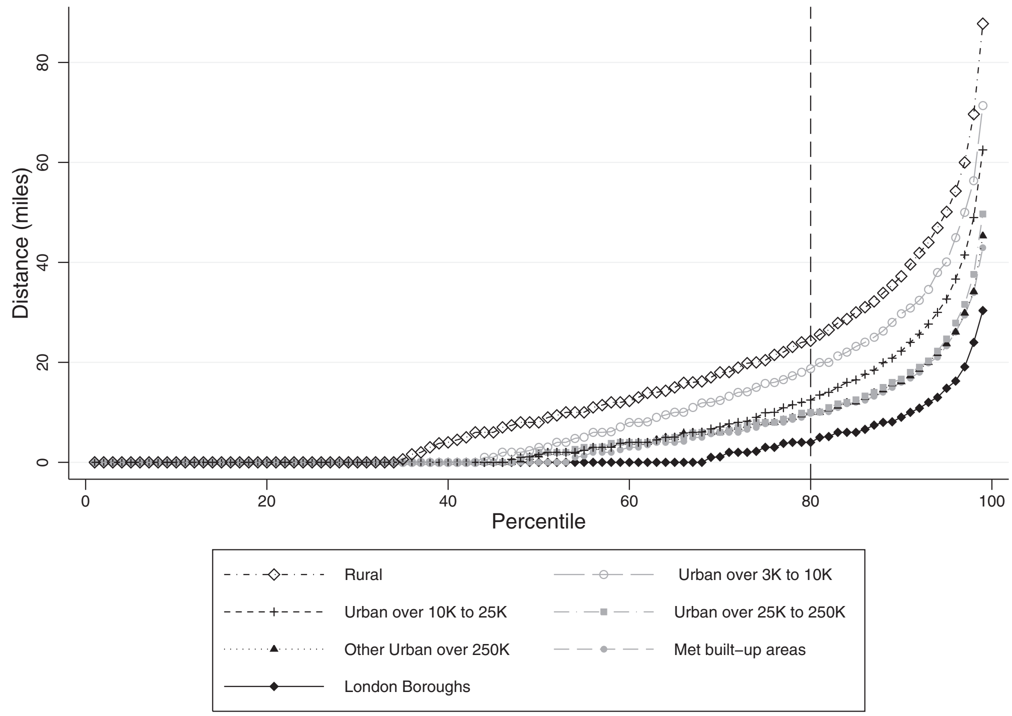

Fig. 1. Percentiles of household weekly car driver distance for food shopping by type of area (miles).

and income are generally not statistically significant. In most areas households with a reference person (HRP) over 60 years old are the most likely to be in the 'top 20%', while having an employed household reference person reduces this probability. Self-reported accessibility to grocery stores does not have a statistically significant association with the outcome, except in rural areas. Most notably, the predictive power of these models is extremely low, with Pseudo-R^2 values in the range of 0.01–0.02.

We conclude that households in the 'top 20%' group are larger, older and more likely to be non-employed than other car-owning households, while also owning more cars per adult. Overall, however, the main take home message is that our sample of 'gross polluters' is not particularly different from other car-owning households in terms of socio-demographics and accessibility.

4.3. Cluster analysis

While previous studies have mostly focused on the determinants of different levels of emissions, in this article we aim to look for variety within the top 20%, highlighting different patterns of 'travel to food shopping' that result in high emissions. We achieve this by clustering households in the analysis sample according to attributes of their weekly food shopping travel. Five dimensions are taken into consideration, as illustrated in Table 1.

First, the overall distance travelled for food shopping, relative to other households in the analysis sample and in the same type of area. This is clearly a crucial factor contributing to the carbon impact of food shopping travel patterns. The second dimension relates to the question whether most of the distance is accounted for by a single, very long-distance trip. The third dimension is the frequency of car driver trips to the shops, as frequency is generally identified as a defining feature of food shopping patterns (Section 2.3). While the first three dimensions only take into consideration car driver trips, the fourth assesses how many food shopping trips are made with alternative modes. The fifth and last dimension ('Shopping intensity') assesses the importance of food shopping relative to other travel purposes, both in terms of car driver distance and of travel time (by all modes). Overall, these five dimensions allow us to give a rich description of households' travel patterns for food shopping, taking into account distance, frequency, modal choice, and the relative importance of food shopping as a travel purpose.

These five dimensions are operationalised with six variables, as described in Table 1. Based on standardised variables and on the pooled sample (2002–2010) we have conducted cluster analysis with the k-means clustering method and Euclidean distance as proximity measure[2]. A four cluster solution was retained as the most satisfactory in terms of distinct clustering (according to the Calinski–Harabasz pseudo-F-statistic). The size of the clusters and their average values on the (unstandardised) input variables are reported in Table 1.

The table shows that the differences between the clusters are mainly determined by the degree to which shopping is concentrated in relatively few journeys across the week, the degree to which the total car mileage accounted for by food shopping is relatively high or low among the analysis sample within each type of area, and the degree to which these trips are undertaken mainly by car or whether other modes are also used.

Using these parameters, two groups of clusters can be identified. Firstly, Cluster 1 ('Single long distance trip', 45% of the sample) can be likened to Cluster 4 ('Long distance trip and alternatives', 7%) on the basis that both are characterised by a high concentration of household car driver miles for food shopping in a single trip. On average, for Clusters 1 and 4, the longest food shopping trip accounts for 49–50% of the total household car driver distance for this travel purpose, suggesting that in most cases a single round trip is responsible for the totality of car travel. Also, in both cases, household car driver distance for food shopping is lower than for

[2] The choice of k-means is motivated by the problems that hierarchical clustering methods encounter with very large data sets such as the one used here, while the use of Euclidean distance allows size displacement to affect similarity. We have checked the robustness of the clustering solution by varying (some of the) input variables, obtaining reassuring results.

Table 1
Cluster size and average values on unstandardised input variables.

		1-Single long distance trip (SLDT)	2-Frequent shopping (FS)	3-Shopping intensive (SI)	4-Long distance trip & alternatives (LDT&A)
	Size	44.9%	37.1%	11.7%	7.3%
Dimension	Input variable				
Distance	Percentile of household car driver distance travelled for food shopping (within analysis sample and type of area)	36	64	64	43
Concentration	Percentage of total household car driver distance for food shopping accounted for by longest trip	50%	28%	34%	49%
Frequency	Total number of household car driver trips for food shopping over the week	3.3	6.8	5.5	3.3
Alternatives	Percentage of household trips for food shopping by modes other than car driver or passenger (including short walks)	0.4%	1.3%	2.3%	40.3%
Shopping intensity	Percentage of total household car driver distance accounted for by food shopping	12%	16%	57%	17%
	Percentage of total household travel time accounted for by food shopping	9%	13%	43%	16%

their 'gross polluting' counterparts in the same areas and food shopping trips by car account for only a small proportion of all car distance travelled. However, there is an important difference between these two clusters in that Cluster 4 tends to supplement these infrequent car shopping trips with a substantial share of trips by alternative modes (40%).

The second pair of clusters is that of Cluster 2 ('Frequent shopping', 37%) and 3 ('Shopping intensive', 12%) characterised by higher frequency (on average approximately 6 car driver trips per week), lower concentration of shopping miles in single trips, and longer distance. However, Cluster 3 ('Shopping intensive') is different from Cluster 2 ('Frequent shopping') in two ways. Firstly, further investigation shows that despite similar frequency, their average trip length is on average higher. Secondly, their food shopping accounts for a large share of household car driver miles (60%) and travel time (40%). In other words, while people in this cluster travel disproportionately long distances for food shopping (partly as a result of frequency, but also because of longer average trip lengths) they do not travel much for other reasons. This contrasts with all the other clusters, where food shopping never accounts for more than 20% of total household car driver distance or travel time, i.e. households travel much for other purposes as well.

While our analysis so far has used pooled data for the years 2002–2010, the dataset makes it possible to trace trends over time. Descriptive analysis suggests that there is no clear and statistically significant change in the size of the clusters over time, with the partial exception of the 'Shopping intensive' cluster, whose size has almost steadily increased between 2002 (8.8%) and 2010 (11.4%).

4.4. Profiling the clusters

In this section we profile the clusters on variables not used in their creation. Table 3, at the end of this section, provides a summary narrative description of the defining characteristics of the four clusters, based on both input variables and descriptive variables.

Table 2 presents the values of socio-demographic and accessibility variables (the same as in Tables A1 and A2 plus mobility difficulties) for the clusters as well as for the analysis sample and the full NTS sample (to allow comparison). It shows that, while most differences between clusters are statistically significant, the largest differences are between Clusters 1, 2 and 4, on one hand, and Cluster 3 ('Shopping intensive'), on the other. Cluster 3 has smaller average household size, fewer children, strong overrepresentation of older households (81% over 50 and 68% over 60 years old) and households with lower income (54% are actually in the two lowest quintiles) or fewer economically active members. Consistent with this, further analysis shows that 57% of this cluster consists of pensioners, as opposed to less than 20% in all others. Also, roughly 40% have at least one member with mobility difficulties walking or using public transport – something which might contribute to their reliance on the car for food shopping. Further correspondence analysis confirms that, for all variables in Table 2 except gender and accessibility, a large percentage of the total inertia (between 77% and 97%) is still accounted for when the classification is simplified by merging Clusters 1, 2 and 4, i.e. most of the association between the classification and socio-demographic variables is due to differences between the 'Shopping intensive' cluster and the rest. In comparison, differences between the remaining clusters are more nuanced, although higher income, female-headed and employed households are particularly overrepresented in the Cluster 1 ('Single long distance trip') group.

As illustrated in Table 2, the percentage of households in the 'top 20%' group reporting that more than 15 min are needed to travel to the nearest grocer by alternative modes (walking or public transport) is just 9%. While this varies between clusters, further exploration shows that, within most types of area, there are no statistically significant differences between clusters on this accessibility variable. This suggests that the differences observed in Table 2 are the result of two facts: first, accessibility is worse in less urbanised areas; second, Cluster 2 ('Frequent shopping') and Cluster 3 ('Shopping intensive') are overrepresented in less urbanised areas (see Fig. 2 below). As a result, Clusters 2 and 3 appear to have

Table 2
Mean values of selected socio-demographics and accessibility variables for the clusters. (HRP: Household Reference Person). Items in superscript indicate which values are significantly different from each other (percentage values: chi square test at the 0.05 level (design-based F). Mean values: ANOVA post hoc analysis – Scheffe test searching for differences among all combinations of groups, at the 0.05 level).

	1-Single long distance trip	2-Frequent shopping	3-Shopping intensive	4-Long distance trip & alternatives	Analysis sample	NTS sample
Female HRP	27.0%[2,3]	23.8%[1]	24.5%[1]	25.1%	25.4%	36.7%
Household size	2.7[2,3,4]	2.9[1,3]	2.0[1,2,4]	2.9[1,3]	2.7	2.4
Households with children	32.1%[2,3]	35.3%[1,3]	9.9%[1,2,4]	33.4%[3]	31.0%	27.0%
Top 2 income quintiles	52.9%[2,3,4]	49.4%[1,3,4]	24.6%[1,2,4]	44.0%[1,2,3]	47.9%	40.0%
HRP over 50 years old	47.8%[2,3,4]	51.2%[1,3]	81.0%[1,2,4]	53.5%[1,3]	53.0%	51.4%
HRP employed	75.4%[2,3,4]	72.3%[1,3,4]	28.7%[1,2,4]	67.5%[1,2,3]	68.7%	60.8%
No. of cars	1.6[2,3,4]	1.8[1,3,4]	1.2[1,2,4]	1.4[1,2,3]	1.6	1.1
Mobility difficulties (foot or bus)	15.7%[2,3]	19.9%[1,3,4]	43.1%[1,2,4]	17.1%[2,3]	20.0%	22.9%
Self-reported journey time time on foot or by public transport (whichever is the quickest) to nearest grocer >15 min	8.1%[2,3,4]	10.7%[1,4]	11.1%[1,4]	3.3%[1,2,3]	9.1%	7.3%

Table 3
Summary description of clusters.

	Cluster description
1. Single long distance trip (SLDT)	Food shopping for households in this cluster tends to be concentrated in a single weekly trip, particularly on Saturdays, with total car distance travelled for this activity ending up being relatively low compared to other 'gross polluters' living in the same type of area. In addition, food shopping accounts for a small proportion of the total distance they travel by car. The infrequent car trips are not supplemented by additional trips using non-car modes Highest economic activity and income and incidence of female-headed households Overrepresented in London
2. Frequent shopping (FS)	Households in this cluster undertake frequent food shopping trips by car and, even though these trips are relatively short, their frequency means they add up to relatively high car mileage compared to other 'gross polluters' living in the same type of area. However, the total distance travelled for food shopping by car still accounts for a relatively low proportion of their overall distance travelled by car. The frequent car trips are not supplemented by additional trips using non-car modes Overrepresented in rural areas
3. Shopping intensive (SI)	Food shopping relatively spread out throughout the week dominates the purpose for which households in this cluster travel. Frequent food shopping trips by car are undertaken and these trips add up to relatively high car mileage compared to other 'gross polluters' living in the same type of area. In addition, the total distance travelled for food shopping by car accounts for a high proportion of overall distance travelled by car. The frequent car trips are not supplemented by additional trips using non-car modes These households tend to be smaller, older, less economically active and with lower income and a high incidence of mobility impairment Overrepresented in rural areas
4. Long distance trip & Alternatives	Households in this cluster tend to undertake a single weekly food shopping trip by car which accounts for only a small proportion of their total car travel. However, this is supplemented by frequent trips using non car modes. Overall, though, people in this group do not spend a very high proportion of their total travel time on food shopping Overrepresented in London

worse accessibility in the aggregate, when in fact there are no statistically significant differences between clusters once the type of area is controlled for.

The uneven representation of clusters across different types of area is illustrated in Fig. 2, showing that 'high frequency' clusters (2 and 3) are overrepresented in rural areas (58% of the analysis sample) and underrepresented in London (34%), while the opposite is true for 'concentrated shopping' clusters (1 and 4) (66% in London, 42% in rural areas). However, there is no clear trend in the intermediate categories (urban areas other than London), where the top 20% is virtually equally split between the two groups of clusters. The overrepresentation of 'high frequency' clusters in rural areas might seem counterintuitive, as one might expect that longer distances in rural areas would lead households to concentrate their food shopping in fewer trips. However, it should be kept in mind that Fig. 2 illustrates only the composition of the top 20% group – it tells us nothing about differences in average food shopping frequency between different areas as a whole[3]. What the figure tells us is that in London, where car food shopping trips are on average shorter, the 'gross polluter' group is composed mostly of households undertaking a single, long-distance car trip for food shopping over the week. By contrast, in rural areas, where car food shopping trips are on average longer, the 'gross polluter' group is composed mostly of households who travel frequently to the shops.

We now turn to some additional trip characteristics of the clusters. Fig. 3 depicts food shopping trip rates by day of the week for each cluster, as well as for the remaining 80% of the dataset (households with no food shopping trips excluded), with different lines representing car driver, alternative mode and all trips confounded. For all clusters, trip rates are higher than for the rest of the population – meaning that high frequency is a crucial characteristic of gross polluting food shopping patterns. The frequent trips undertaken by Cluster 3 ('Shopping intensive') are relatively evenly spread out throughout the week whereas for other clusters, trips are mainly concentrated on Saturdays, particularly the long distance single trips of Cluster 1 ('Single long distance trip'). Also, households in Cluster 4 ('Long distance trip & alternatives') have trip rates comparable to Cluster 2 ('Frequent shopping') once alternatives are factored in. This explains why a similar share of their time is devoted to food shopping travel (cfr. Table 1).

Table 3 summarises the defining characteristics of the four clusters, based on both input variables and descriptive variables.

4.5. CO_2 emissions

Differences in car driver distances between the clusters explain the large differences in weekly CO_2 emissions reported in the left half of Table 4, showing higher values for frequent shopping than single trip clusters. When considering *per capita* emissions the 'Shopping intensive' cluster clearly stands out with 6.9 kg CO_2

[3] As a matter of fact, household trip rates for food shopping are indeed lower in rural areas (4.23 trips per week) than in most urban areas, with the notable exception of London (3.79).

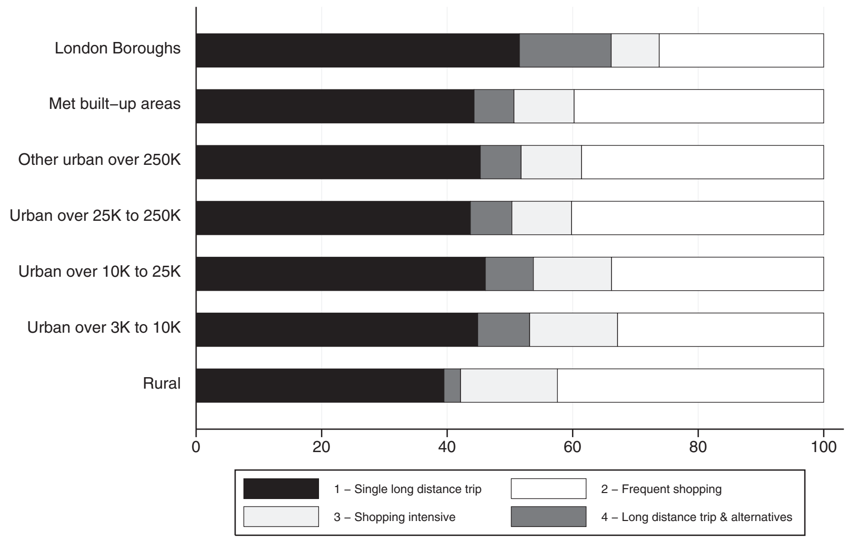

Fig. 2. Size of clusters in the 'top 20%', by type of area. Chi square test (design-based F): $p < 0.01$.

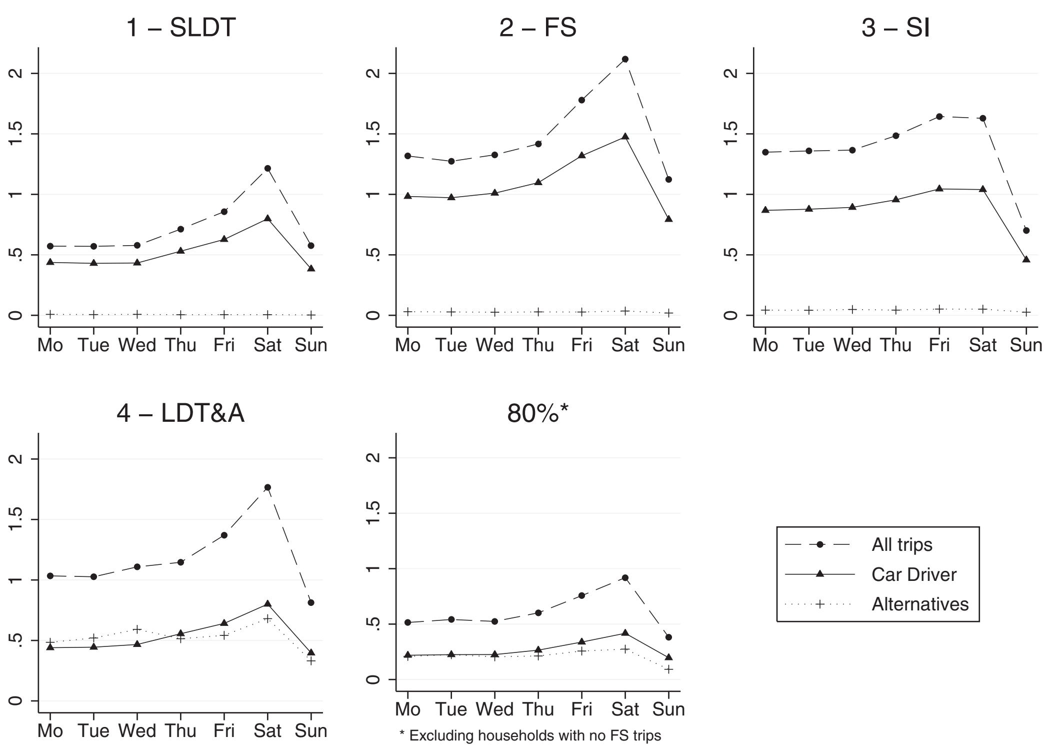

Fig. 3. Trip rates for the clusters and other households with at least one food shopping trip, by day of the week.

per week (four times the average in the full NTS sample), as a result of lower household size.

The right half of the table shows the overlap between the clusters and other 'top 20%' groups and it should be read as follows. 96.5% of households in Cluster 2 ('Frequent shopping') also belong to the top 20% of CO_2 emissions *for food shopping travel* within their type of area. Similar percentages are observed for the other clusters, with the exception of Cluster 1 ('Single long distance trip'). This confirms the large overlap between the top quintile of households in terms of car travel distance for food shopping and the top quintile of households in terms of resulting CO_2 emissions. This is not surprising since, as noted above, CO_2 emissions are closely tied to car travel distance. The lower value for Cluster 1 is explained by lower distances and CO_2 emissions as compared to other clusters, confirming that 'single-long distance trip' patterns of weekly food shopping are relatively less polluting.

On the other hand, the table shows that only 37% of households in Cluster 2 ('Frequent shopping') also belong to the top 20% of CO_2 emissions *for all travel* within their type of area (note that air travel is excluded). Similar percentages are observed for other clusters, with the notable exception of Cluster 3 ('Shopping intensive'), for which the overlap is just 1.3%. Two conclusions can be drawn from this. First, only a minority of the top 20% households considered in this study are 'gross polluters' when all travel purposes (and not just food shopping) are considered. This suggests that for most households high travel emissions for food shopping are offset by lower emissions for other purposes. Second, the emission profile of Cluster 3 is particularly interesting: while these households

Table 4
Average CO_2 emissions and overlap between top 20% subsamples. Items in superscript indicate which values are significantly different from each other (percentage values: chi square test at the 0.05 level (design-based F). Mean values: ANOVA post hoc analysis – Scheffe test searching for differences among all combinations of groups, at the 0.05 level).

	CO_2 per week (kg), food shopping travel		Share of households in top 20% of CO_2 emissions (within type of area)	
	Household	*per capita*	Food shopping travel	All travel
1-Single long distance trip	$6.3^{2,3,4}$	$2.9^{2,3}$	$79.5\%^{2,3,4}$	$37.4\%^{3,4}$
2-Frequent shopping	$9.8^{1,3,4}$	$4.1^{1,3,4}$	$96.5\%^{1,3,4}$	$37.0\%^{3}$
3-Shopping intensive	$12.0^{1,2,4}$	$6.9^{1,2,4}$	$93.6\%^{1,2,4}$	$1.3\%^{1,2,4}$
4-Long distance trip & alternatives	$7.6^{1,2,3}$	$3.2^{2,3}$	$90.7\%^{1,2,3}$	$33.7\%^{1,3}$
Analysis sample	8.3	3.8	88.1%	33.1%
NTS sample	3.5	1.7	20.0%	20.0%

have the highest emission levels for food shopping travel, virtually none of them can be defined as a gross polluter overall. This is consistent with the finding that they do not travel much for reasons other than food shopping.

5. Discussion

In this paper, we have investigated what are the patterns of weekly food shopping travel among the 20% of households responsible for most of it. This builds on previous research suggesting that the distribution of transport emissions is strongly skewed. Our findings suggest that the '60-20' rule (Brand and Preston, 2010) holds even when a single trip purpose is considered and the degree of urbanisation is controlled for. This contrasts with Brand and colleagues' finding that emissions from shopping and personal business are more equally distributed than those arising from other travel purposes (2013, p. 162).

At the same time, several findings of this study are challenging for the current research emphasis on the determining role of socio-demographic and spatial factors. Therefore, in interpreting our findings, we draw on the conceptual toolkit of practice theories, discussing possible relationships within the 'complex of practice' that connects food shopping with eating, cooking and food preservation practices (Hand and Shove, 2007; Warde, 2013). Clearly, such relationships cannot be explored directly within the framework of this study. We can, however, discuss the results in light of previous findings and suggest directions for further research.

With regard to socio-demographics, we find that there are only minor differences between the 'top 20%' group and other households, once car ownership is controlled for. Also, the profiles of three of the four clusters of gross polluters are virtually indistinguishable and, while that of the most polluting cluster is very distinct, the overrepresentation of retired, poorer households clearly goes against expectations, although it is consistent with Brand and colleagues' finding that workers are less likely to be high emitters for shopping and personal business (2013). Overall, this suggests that factors found to explain high transport emissions in previous studies are less important when focusing on food shopping (and controlling for the built environment), i.e. a broader range of people are recruited in gross-polluting variants of food shopping practices.

With regard to spatial factors, while the study has deliberately controlled for urbanisation, it is worth noting that there are no statistically significant differences between the 'top 20%' and other households in terms of accessibility to grocery shops. This is consistent with the results of Brand et al. (2013), who found no significant effect of home-retail centre distance on transport emissions for shopping/personal business. Also, in our study the large majority of gross polluters live within 15 min (by foot or bus) from the next grocery shop, and the different patterns of food shopping travel within the top 20% are not associated with accessibility. This suggests that while the built environment is a crucial determinant, for most households long travelled distances do not result from a lack of local stores.

Indeed, our findings show that for approximately half of the top 20% (clusters 1 and 4), most of the emissions arise from a single long distance trip by car, typically on Saturday. This is consistent with previous studies showing that people are willing to travel much further than the closest food stores (Handy and Clifton, 2001; Krizek, 2003) for reasons that include price, quality or variety of goods and store environment. While this often leads authors to the not-so-surprising conclusion that household preferences are not entirely determined by proximity and that food is more than just a convenience good, we are more interested in observing that there are links between at least some of these reasons and the eating practices of households. For example, while there is increasing normative value attached to the consumption of fresh fruits and vegetables (Hand and Shove, 2007; Waitrose, 2014), buying them often requires travelling longer distances (Sheats et al., 2014), as does purchasing 'healthy' and 'sustainable' food (Handy and Clifton, 2001; Johnston and Szabo, 2011). On the other hand, previous studies have highlighted the link between special offers, bulk-buying and food freezing (Hand and Shove, 2007; Shove and Southerton, 2000), and this can result in long travel distances to retailers offering discounts.

On the other hand, our findings challenge simple oppositions such as that between sustainable, frequent food shopping travel by alternative modes on shorter distance trips and unsustainable, infrequent bulk-buying by car to more distant stores, by showing that patterns characterised by frequent car trips are particularly polluting. This is important in light of claims that food shopping patterns in the UK are shifting away from 'one-stop' out-of-town supermarkets towards 'convenience' local shops (Wrigley and Lambiri, 2014). The relevance of *high frequency* is reflected in several findings: first, all clusters have higher trip rates than other households making at least one trip for food shopping in the survey week (regardless of mode). Also, for roughly half of gross polluters (clusters 2 and 3) it is frequency, more than average trip length that results in large overall travelled distance, and these groups have the largest emissions. Again, previous research has suggested that eating practices centred on fresh food are associated with frequent shopping (Hand and Shove, 2007; Shove and Southerton, 2000). Similarly, previous studies (Handy and Clifton, 2001; Johnston and Szabo, 2011) suggest that buying 'local' and 'organic' is currently not easily accomplished with one-stop shopping, and might require more frequent and long distance travel in order to access the different shops where (some of) the alternative products are sold. Finally, the 'long distance trip & alternatives' cluster shows that the combination of a Saturday supermarket run by car and 'top up' shopping trips during the week might also result in high levels of emissions. Incidentally, this also confirms that having access to stores by alternative modes does not preclude car trips to further destinations.

The 'Shopping intensive' cluster shows that patterns of frequent (and not-so-short) car trips to the shops are more common among older and poorer households who do not travel much for other reasons. Previous qualitative findings on older people's shopping provide us with a list of possible reasons for travelling to distant shops: Curch and Thomas (2006) find that the elderly place particular importance on the quality of product and service (including courteousness), and have difficulties in navigating stores (related to mobility difficulties), resulting in high store loyalty. On the other hand, several studies explain high shopping frequency among the elderly with the fact that it is for them a social and a leisure activity, a welcome opportunity to leave the house and is frequently conducted together by spouses (BBSR, 2011; Curch and Thomas, 2006; Schmöcker et al., 2008). Indeed, existing qualitative evidence suggests that time- and carbon-intensive practices of food shopping travel have good chances to occupy the time freed up with the transition to retirement (Curch and Thomas, 2006; Hand and Shove, 2007). While the reasons for this are unclear, this contrasts with the current emphasis of sustainable practices research on the energy consumption increases resulting from time-saving devices and hurried lifestyles (Jalas, 2005; Shove, 2003). Another possible explanation for frequent shopping is discount-chasing, i.e. travelling to different shops in order to exploit the best price promotions (Curch and Thomas, 2006). This might explain the diffusion of these patterns among older and low-income households who have limited financial resources. Overall, the importance of understanding travel patterns in this cluster in magnified by the rapid ageing of the car mobile population, which might explain why it increased in size between 2002 and 2010.

6. Conclusions

In this article, we have presented a study inspired by previous research on the unequal distribution of GHG emissions, interpreting the results in light of social practices research. The implications of our findings for sustainable transport policy, however, are quite different depending on which approach is adopted: this is why in this section, we proceed to explore them separately.

From a practice theory perspective, as Shove and Spurling argue, "the challenge is one of imagining and realising versions of normal life that fit within the envelop of sustainability" (2013, p. 1). Our study has shown that there is a wide variation in the climate impact of food shopping practices, identifying four gross polluting travel patterns and discussing their possible relationships with eating practices. The fact that the current practices of the large majority of households are already relatively sustainable illustrates the potential for emission reductions – but also the dangers if the most polluting patterns are adopted by wider sectors of the population (Girod and de Haan, 2009). A rough calculation based on the data used in this study suggests that an adoption by the fourth quintile of the food shopping travel patterns of the top 20% would result in +44% CO_2 emissions for food shopping. In that sense, the question really is one of targeting and taming the few (variants of) *practices* that are responsible for most of the environmental damage.

Our findings suggest that, while compact city and accessibility planning policies will remain key to reduce food shopping travel emissions, they are unlikely to be sufficient. Notably, the *frequency* (and not just the distance) of trips emerges as a problem. To be sure, frequent trips are not a problem if they are made by low carbon modes, and compact and accessible neighbourhoods can encourage use of these modes. However, our analysis suggests that patterns of *frequent car travel* to the shops are relatively common in all types of area, and have a disproportionate impact in terms of GHG emissions.

This leads to consider whether the concentration of food shopping trips would be a realistic policy goal. In theory this may pay big rewards, as modelling findings for Germany (Aamaas et al., 2013) suggest that the condensation of all motorised shopping

Table A1
Logistic regression model for the probability of belonging to the 'top 20%' group, based on full NTS sample.

Variable	Level	Logit coefficients [standard errors] for being in top 20% of car driver distance for food shopping travel ($^{*}p < 0.05$)						
		London boroughs	Met built-up areas	Other urban over 250 K	Urban over 25–250 K	Urban over 10–25 K	Urban over 3–10 K	Rural
Household size		0.412 [0.038]*	0.423 [0.039]*	0.414 [0.036]*	0.419 [0.030]*	0.332 [0.052]*	0.440 [0.058]*	0.330 [0.040]*
Any child under 16 (reference category: no)	Yes	−0.304 [0.130]*	−0.378 [0.115]*	−0.453 [0.115]*	−0.560 [0.090]*	−0.311 [0.142]*	−0.685 [0.164]*	−0.460 [0.112]*
Sex of HRP (reference category: male)	Female	−0.294 [0.088]*	−0.257 [0.084]*	−0.254 [0.074]*	−0.228 [0.057]*	−0.346 [0.106]*	−0.418 [0.112]*	−0.374 [0.078]*
Age of HRP (reference category: 16–29 years)	30–59 years	0.562 [0.188]*	0.327 [0.144]*	0.154 [0.137]	0.293 [0.114]*	0.248 [0.222]	0.147 [0.246]	0.178 [0.172]
	>60 years	0.896 [0.198]*	0.874 [0.157]*	0.446 [0.153]*	0.606 [0.126]*	0.323 [0.229]	0.310 [0.270]	0.215 [0.188]
Employment status of HRP (reference category: not employed)	Employed	−0.120 [0.124]	−0.032 [0.111]	−0.257 [0.116]*	−0.077 [0.080]	−0.200 [0.155]	−0.142 [0.144]	−0.241 [0.103]*
Real household equivalent income (reference category: lowest real income)	Second quintile	0.464 [0.153]*	0.098 [0.118]	0.070 [0.123]	0.296 [0.089]*	0.314 [0.148]*	0.203 [0.175]	−0.054 [0.114]
	Third quintile	0.549 [0.148]*	0.293 [0.126]*	0.316 [0.120]*	0.321 [0.094]*	0.590 [0.153]*	0.257 [0.168]	0.197 [0.119]
	Fourth quintile	0.570 [0.151]*	0.180 [0.134]	0.409 [0.127]*	0.396 [0.096]*	0.470 [0.182]*	0.112 [0.181]	0.123 [0.122]
	Highest real income	0.236 [0.162]	0.318 [0.144]*	0.237 [0.136]	0.375 [0.104]*	0.531 [0.195]*	−0.037 [0.198]	0.036 [0.127]
Cars per adult in household		2.143 [0.122]*	1.825 [0.122]*	1.503 [0.102]*	1.475 [0.069]*	1.117 [0.132]*	1.205 [0.119]*	0.773 [0.082]*
Self-reported journey time on foot or by public transport (whichever is the quickest) to nearest Grocer (reference category: <15 min.)	>=15 min	0.272 [0.244]	0.218 [0.185]	0.251 [0.159]	0.172 [0.123]	−0.006 [0.207]	0.222 [0.202]	0.278 [0.067]*
Constant		−4.259 [0.227]*	−4.009 [0.199]*	−3.574 [0.182]*	−3.839 [0.151]*	−3.224 [0.304]*	−3.301 [0.308]*	−2.771 [0.232]*
McFadden's Pseudo R^2		0.16	0.12	0.08	0.08	0.07	0.07	0.04
N		4741	5962	6422	11,204	3499	3189	6489

trips to one return trip per week would result in a reduction of 7% in the climate impact of all transport. In this context, one may ask whether the recent diffusion of online shopping and home delivery could be steered towards this goal. So far, online shopping has been discussed as a possible 1:1 substitute to physical travel to the shops (Edwards et al., 2010). A different approach would exploit it to engender food shopping frequency reductions (both physical and online). While a discussion of this point is beyond the scope of this article, let it just be noted that current policies of offering cheap flat rates for home delivery might encourage the opposite outcome, i.e. more frequent shopping. Given the GHG emissions associated with deliveries (Edwards et al., 2010), this might result in increased emissions for food shopping.

Of course, any policy intervention on food shopping will need to consider the related practices of eating and cooking. This nexus is an area where trends might be rapidly changing. While neither our analysis nor official figures (DfT, 2014) confirm this, recent market research reports (Waitrose, 2014) suggest that food shopping frequency might be increasing in Britain as a result of a switch to less planned and more spontaneous meals. The rise of practices such as vegetarianism, flexitarianism, local and organic eating might also, as we argued, result in increased shopping frequency. Importantly, this is a field where governments are active, with initiatives such as '5 a day' in the UK, providing an illustration of how non-transport and non-energy policies have a potentially strong bearing on transport energy demand. Whether the overall environmental impact of such trends is positive is a challenging empirical question, which should take into account the trade-offs between transport and other sectors (e.g. food production and waste). The findings of this study, however, suggest that if increased frequency is not accompanied by a modal shift to active travel, this could result in increased transport emissions.

Studies on the distribution of carbon emissions are generally motivated by social justice concerns for the distributional implications of much discussed broad-brush policies such as carbon taxes and rationing. From this perspective, the findings of this study highlight that while gross polluters for transport as a whole are clearly concentrated among privileged social groups, this is less true when zooming in on a specific travel purpose such as food shopping. This has two implications: on one hand, targeting the polluting few might inadvertently lead to neglect large potentials for carbon reductions *in specific practices* that are found across the whole population. On the other hand, carbon reduction policies of the type described might threaten the carbon intensive practices of less well-off households, such as those in the 'Shopping intensive' cluster. If such practices are instrumental to effective social participation (e.g. by providing occasions for sociability), this could be considered unjust, especially if the overall carbon emissions of the household are low.

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Table A2
Logistic regression models for the probability of belonging to the 'top 20%' group, for households owning at least one car.

Variable	Level	Logit coefficients [standard errors] for being in top 20% of car driver distance for food shopping travel ($^{*}p < 0.05$)						
		London boroughs	Met built-up areas	Other urban over 250 K	Urban over 25–250 K	Urban over 10–25 K	Urban over 3–10 K	Rural
Household size		0.157 [0.045]*	0.204 [0.044]*	0.236 [0.040]*	0.262 [0.033]*	0.125 [0.057]*	0.300 [0.058]*	0.239 [0.042]*
Any child under 16 (reference category: no)	Yes	−0.043 [0.128]	−0.076 [0.113]	−0.206 [0.113]	−0.314 [0.088]*	0.026 [0.141]	−0.458 [0.160]*	−0.327 [0.112]*
Sex of HRP (reference category: male)	Female	−0.192 [0.090]*	−0.104 [0.085]	−0.140 [0.074]	−0.090 [0.058]	−0.177 [0.105]	−0.282 [0.115]*	−0.288 [0.079]*
Age of HRP (reference category: 16–29 years)	30–59 years	0.474 [0.196]*	0.360 [0.149]*	0.152 [0.139]	0.261 [0.113]*	0.306 [0.212]	0.072 [0.251]	0.176 [0.173]
	>60 years	0.695 [0.208]*	0.829 [0.170]*	0.329 [0.159]*	0.521 [0.128]*	0.374 [0.225]	0.158 [0.281]	0.193 [0.191]
Employment status of HRP (reference category: not employed)	Employed	−0.291 [0.126]*	−0.138 [0.108]	−0.375 [0.117]*	−0.176 [0.080]*	−0.270 [0.145]	−0.225 [0.143]	−0.275 [0.101]*
Real household equivalent income (reference category: lowest real income)	Second quintile	0.344 [0.169]*	−0.040 [0.124]	−0.065 [0.129]	0.156 [0.092]	0.132 [0.158]	0.041 [0.181]	−0.124 [0.118]
	Third quintile	0.318 [0.157]*	0.013 [0.126]	0.121 [0.121]	0.124 [0.094]	0.287 [0.158]	0.049 [0.171]	0.089 [0.120]
	Fourth quintile	0.382 [0.155]*	−0.004 [0.130]	0.223 [0.127]	0.241 [0.094]*	0.309 [0.182]	−0.055 [0.180]	0.019 [0.124]
	Highest real income	0.055 [0.161]	0.226 [0.140]	0.111 [0.133]	0.296 [0.101]*	0.397 [0.189]*	−0.156 [0.197]	−0.031 [0.126]
Cars per adult in household		0.335 [0.151]*	0.310 [0.139]*	0.400 [0.120]*	0.379 [0.091]*	0.008 [0.155]	0.257 [0.161]	0.265 [0.103]*
Self−reported journey time on foot or by public transport (whichever is the quickest) to nearest Grocer (reference category: <15 min.)	>=15 min	0.316 [0.259]	0.272 [0.182]	0.268 [0.165]	0.159 [0.122]	0.093 [0.208]	0.215 [0.195]	0.275 [0.068]*
Constant		−1.783 [0.289]*	−2.027 [0.244]*	−1.948 [0.221]*	−2.301 [0.181]*	−1.657 [0.336]*	−1.847 [0.362]*	−1.964 [0.253]*
McFadden's Pseudo R^2		0.02	0.02	0.01	0.01	0.01	0.02	0.02
N		2912	3991	4816	8451	2709	2583	5799

Archive at the University of Essex, Colchester. The responsibility for the analysis, interpretation and all conclusions drawn from the data lies entirely with the authors. The authors would like to thank members of the DEMAND Research Centre and two anonymous reviewers for their valuable comments on previous versions of this paper.

Appendix A

See Tables A1 and A2.

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